MEDICAL IMAGE SEGMENTATION USING TEXTURE DIRECTIONAL FEATURES

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Abstract - **Medical image segmentation can often be performed through tissue texture analysis. One of the most recent and interesting ideas to do that is to take into account the distribution of local maximum orders. We have followed up this idea by using directional maximums and we have applied it to tissue differentiation. Two problems are emerging now: one is the identification of a given texture (labeling) and another one is the characterization of the different areas within images (segmentation). In this paper, we present our new approach for texture representation and analysis, and we point out the advances and problems involved in the image segmentation process.**

Keywords - **Texture, image segmentation, directional maximums**

I. INTRODUCTION

Texture is directly related to the distribution of pixels that belong to the neighborhood of a given location. Practically, we need to define a window that produces a local view of this location, and a set of measures on this window.

For a long time, it has been conjectured about these measures that statistical moments on the pixels of this window would permit to discriminate different textures [1]. This conjecture has been invalidated by A. Gagalowicz [2] who produced two visually different textures with identical statistical moment values. Consequently, other functions, such as energy or entropy for instance, have been studied [3].

Texture discrimination is then provided through a classification in the representation space (i.e. the space in which each coordinate is associated with one of the measures).

One of the last pieces of research work in this field has been developed by S. Bonnevay on the study of ordered maximums [4]. An nth order maximum is a value that is a maximum up to the nth neighbors (e.g. a value is a "1st order maximum only" means that it is greater than all the connected pixels but not greater than all the next ones). Counting up these ordered maximums in the window gives a very interesting evaluation of the region's granularity. But this evaluation doesn't consider directional textures.

We have developed a new approach that consider this directionality and provides a visual means to evaluate the similarity of two textures in the representation space. As a consequence, this visual means can be used as a support to design a relevant dissimilarity function in order to discriminate these two textures. These works have been presented recently in [5].

II. A NEW APPROACH

Our approach consists in studying the directional distribution of maximum orders in the window. The result is a surface that provides a normalized representation of this distribution. Finally, the texture comparison problem is transposed to a surface comparison one that can be process more easily than a data classification in the representation space.

Let us consider an area which is supposed to be made of a given texture. For each pixel of this area – those which are close to its border – we determine, for all directions, if it is a maximum and, in this case, what is its order.

We work in a discrete space and we are interested only in local properties. These two remarks led us to define a mask that provides the neighboring order for a set of Nd directions and No orders. This mask is a (2.No+1) by (2.No+1) array. Practically, we define eight directions, the 8-connectivity ones, (i.e. Nd = 8) and we fill a 13 by 13 pixel mask (No = 6) as illustrated below (Figure 1):

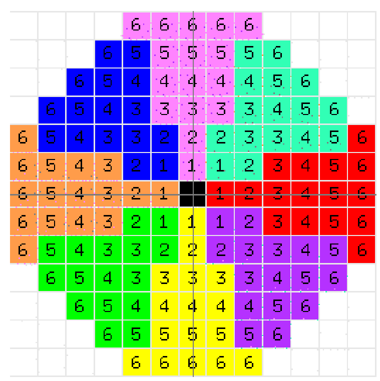

Figure 1: The mask giving the neighboring order

Then, let us consider a region that is supposed to be filled with a given texture (this region can be a whole image if it is a learning set, or a N by N window in a specific image when trying to provide a segmentation).

We initialize Nd arrays of No integers with the 0 value. As written before, for each pixel, we determine its order in each direction (if it is not a maximum we consider its order is 0) and we increment the corresponding values in the Nd arrays. At the end of the process, these arrays contain the number of nth order maximums in each direction. At this time, we normalize these values by dividing them by the number of points.

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We note that these values can be considered as cumulated ones (i.e. if a pixel is a nth order maximum in a given direction, it is also a 1st order, a 2nd order, …, a (n-1)th order maximum in this direction): thus, each array contains decreasing values.

Then, we can characterize and visualize a texture (Figure 2) as a set of Nd curves (Figure 3) or as triangulated surfaces (Figure 4) that can be smoothed (Figure 5).

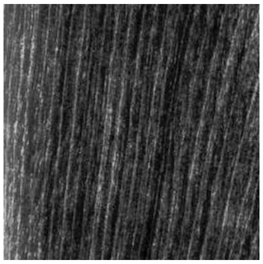

Figure 2

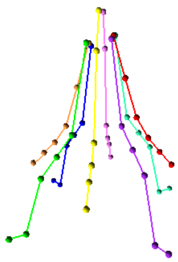

Figure 3

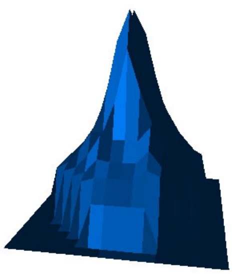

Figure 4

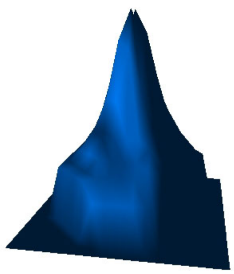

Figure 5

III. TEXTURE DISCRIMINATION

Before going through the methods to compare surfaces associated with different textures, let us visualize an example in which two textures can be discriminated with this approach, although they are not visually very different.

The images below show the differentiation of liver's and spleen's textures. This example has been taken only as an illustration of our approach because other criteria such as organ location and morphological properties could be used to provide a segmentation.

Figure 6 shows us a CT scan with the two tissues.

Figure 6

In figure 7, we have colored the areas – red for the liver and blue for the spleen – on which the texture has been analyzed using our approach.

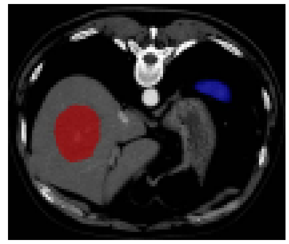

Figure 7

We obtain the red (for liver) and blue (for spleen) surfaces (Figure 8).

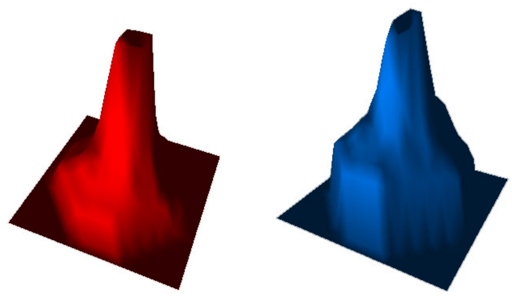

Figure 8

This approach can be considered as a "Scientific Visualization" one because the associated representation (using surfaces) helps us to efficiently understand and analyze the initial data set (the CT scan image, in which textures are not easy to discriminate).

Going further in this way implies to develop visual tools to enable such a comparison but also objective tools to measure dissimilarities between the two surfaces.

Let us first consider "visual tools". Figure 9 shows us the two sets of curves and the two surfaces. These pictures do not show very well all differences because they are static images; but making them rotate provides an interesting visual evaluation of such differences (we can also use transparency for the surfaces).

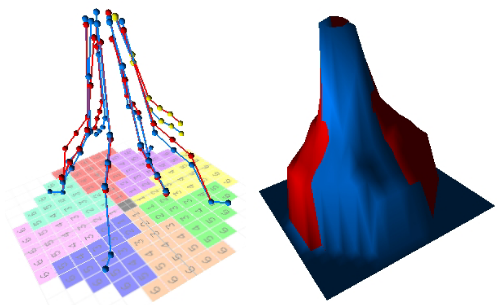

Figure 9

Let us now consider the "quantitative surface comparison". Simple tools can be developed such as those using the value differences (displayed as height differences) – e.g. considering the dissimilarity criterion as the sum of their absolute values or their maximum. But more sophisticated tools also need to be developed in order to analyze their shape and to try to find invariant properties that could characterize "texture classes".

IV. APPLICATION TO MEDICAL IMAGES

As an illustration, we propose to analyze images of a kidney containing a cancerous tumor (Figure 10).

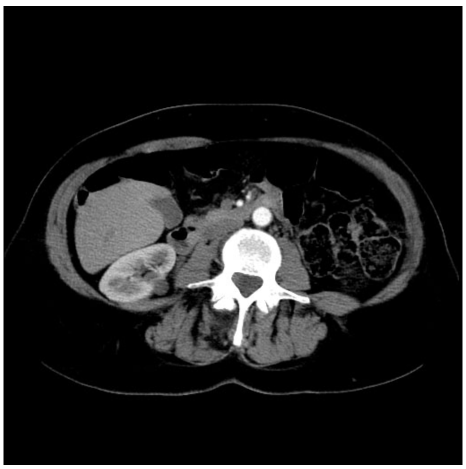

Figure 10

We have colored the healthy tissue in pink and the tumor in red (Figure 11).

Figure 11

On the left part of Figure 12 we can see the curves corresponding to the healthy tissue and on the right part those corresponding to the cancerous one.

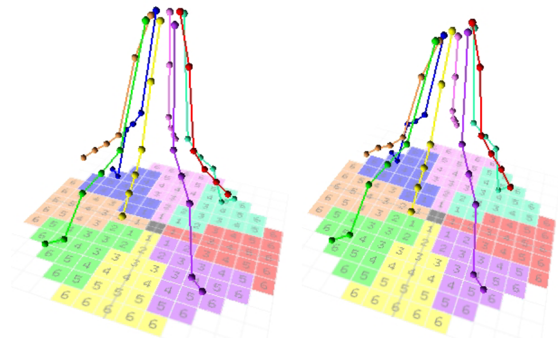

Figure 12

It is displayed using smoothed surfaces (healthy tissue is in blue and cancerous one in red) in Figure 13.

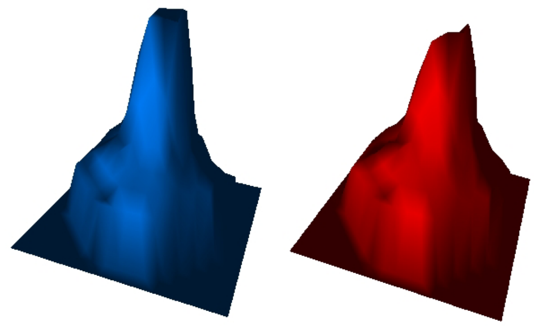

Figure 13

And both surfaces in Figure 14.

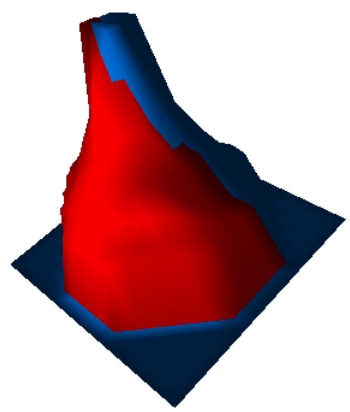

Figure 14

V. TOWARD IMAGE SEGMENTATION

This approach can be taken as a support to provide an image segmentation.

An image can be considered as set of textured areas and transition areas. We would like to find the textured areas in order to identify and to label them (with the help of the

context). And then, using this information, we would like to find in a precise way the border of these areas.

The first step of this process consists in finding areas that would contain the same texture. In order to do that, we perform the following one: we consider a small region (of a given size – e.g. a 50 by 50 square) centered on each pixel of the image; we compute the surface associated with each of the pixels (it is not a very long process because most computations are common to overlapping regions); we study the evolution of the surface; and we group all the points which have similar surfaces.

If fact, it is typically a "split and merge" process. For instance, let us consider the split process: on a given region, we compute the mean surface and we evaluate the similarity of all surfaces (corresponding to each point) with the mean one. This evaluation leads to a global evaluation of the region and eventually to a split (if it is not coherent enough).

In this way, we obtain a partition of the image into coherent areas (some of them being made of one pixel). Big connected areas are then selected as relevant features: they provide a reliable support for the image segmentation.

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